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Prediction of Toxic Gases Using Intelligent Multi-sensors Combined with Artificial Neural Networks.

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Abstract: *The security of monitor indoor air quality using sensors is not yet widespread. However, it is an efficient way to control the toxic gazes coming from large industrial facilities when traditional instrument are not usable especially in low concentration. This paper presents the prediction's power of toxic gases using neural networks MLP off-line type. Back propagation algorithm was used to train a multi-layer feed-forward network (descent gradient algorithm).The data used in this work are stemming from a system of intelligent multi-sensors analysis and signal processing in order to detect hydrogen sulfide(H_2S), NO_2 (nitrogen dioxide) and their mixture (H2S-NO_2) in low concentration (one ppm).The successful results based on different accuracy in terms of statistical criteria, approve the robustness of our developed model that gives a certain power for electronic nose prediction .*

Keywords: *Toxic gases, Artificial Neural Networks, Multi-Layer Perceptron, off-line learning, prediction.*

I. Introduction

Predicting the indoor air pollution is one of the most important steps in the air quality management for general security [1-3] .The toxic gases have been considered as an important challenge for the researchers in the both parts such as the development of valid instrument and the intelligent methods [4]. During the recent decades, different chemical sensors have been shown to be valid instruments used in many engineering applications to control the toxic gases, also it can work on-line without sample pretreatment [4] jointly, the non-linear mathematical model has been added to the prediction tools with the name of artificial neural network, for the following reasons for instance, the relative newness of the sensor, little is known about its dynamic properties in addition to solving nonlinear problems.

The neural network model used in this study was a multilayer Perceptron (MLP) off-line type that learns using an algorithm called back propagation [5-8]. For this, we selected carefully the topologies, activation functions and their coefficient which is the source of our MLP power model [9-13], this novel approach addresses and solves the complex problems of indoor air pollution[14-15],Such as prediction of the toxic gases detected by electronic nose in low concentration. This small database used in this work are stemming from a system of intelligent multi-sensors TGS type (called electronic noses) based on metal oxide analysis and signal processing in order to detect hydrogen sulfide(H2S), NO2(nitrogen dioxide) and their mixture (H2S-NO2) in low concentration (one ppm), included only 160 from 180 samples for optimizing information size [16-18].

The aim of this paper is to use the method (MLP) off-line type to develop a robust model that is able to predict these three toxic gases in the same conditions by comparing some previous researches in term of statistical criteria.[16,19-20].

The remainder of this paper is organized as follows: in the next section, we introduce both materials and methods that deal mainly with feature extraction and database used in this study. The following two sections specify respectively the supervised prediction problem and the algorithm previously mentioned. In particular, we expose the experiments used to select the best parameters for our model that possesses satisfactory predicting performance.

The section IV, concerned with presentation of results and discussion, especially giving much attention to results of the topology with only one hidden layer. Finally, the last section concluded this paper, it is concerned with the power of this model for air security by characterizing information made by intelligent multi-sensors (electronic nose).

II. Materials and Methods

II.1. Features Extraction

The features obtained data analysis were extracted from the temporal responses of the sensor array realized by [16-17] for the detection of the toxic gases H_2S (hydrogen sulfide), NO_2 (nitrogen dioxide) and their mixture (H_2S-NO_2). The sensor array comprise six TGS-XX (with XX = 800, 813, 822, 825, 832 and 2105), Taguchi Gas Sensor obtained from Figaro Engineering, Incorporation [21]. We are concerned with better exploitation of information obtained from this experiment. For this, we deal with first three basic representative features (G0, Gs, dG/dt) from the response signal extracted with ignorance of the fourth feature (A).

• G0: the initial conductance of a sensor calculated as the average value of its conductance during the first minute of a measurement.

• Gs : the steady-state conductance calculated as the average value of its conductance during the latest minute of a measurement.

• dG/dt : the dynamic slope of the conductance calculated between 2 and 30 to50 minutes of a measurement.

• A: the conductance curve in an interval time defined between 2 and 31 minutes of measurement. this area was calculated by the trapeze method.

This corresponds to a phase where a fast increase of sensor conductance is observed [16-18].

These three features were extracted from the response of each sensor. Since there were 6 sensors within the array, each measurement was described by 18 features.

II.2.MLPANN model and Training methods.

The artificial neural network is a type biologically inspired mathematical model, based on the functioning of the human brain. Neural network typology consists of successive layers such as one input, output and a number of hidden layers with a certain number of active neurons connected by feed forward which are associated adjustable weights.[22-25].for the input and hidden layers used a sigmoid and a purelin activation function, respectively. Input includes 18 units (variables) from 6 sensors each one with three variables:G0,dG/dt ,Gs(6x3), output contains one node that encoded three gases class evaluated as follows 1 for NO_2, 2 for H_2S and 3 for NO_2.H_2S(mixture) .Also ,we are varying number of hidden layers and number of units in each hidden layer in order to optimize our best MLP structure .

This model implicated through dataset, which are randomly divided into two bases: training base (80%) and testing base (20%).The first base which is training set (80%), validation set (20%) and test set (20%). The simulation set was used to select the best network on the basis of the network's error performance .the validation of this performance is meticulously on the basis of important parameters [26] such as mean square error (MSE),not only error but also is used as the stopping criterion.

II.2.1. Gradient descent

A gradient descent-based optimization algorithm such as backpropagation the most common method used to adjust the connection weights in an MLP iteratively in order to minimize an error function [22-26]. Generally the error function used is the Mean Square Error (MSE): where it is the target, y is the output, and MSE is the error function. The errors calculated at the output units are propagated backward to units in other layers. In order to minimize the error occurred in backpropagation phase, the value of each weight is updated. [27-32]

$$y_k = \left(\sum_{j=1}^{n_K} w^2{}_{jk}\, f\left(\sum_{i=1}^{n_i} w^1{}_{jk}\, x_i^0 + b_j^i\right)\right) \text{ , for } 1 < j < n_k \text{ and } 1 < k < m \qquad (3.1)$$

Where W_{ij}^1 and $W^2{}_{jk}$ denote the weights between input and hidden layers, and weights between hidden and output layers, respectively.

$b^1{}_j$ and $x^0{}_i$ supplied to the input layer, respectively. n_i, n_h, and m are the number of input nodes, hidden nodes and output nodes, respectively. f(•) is the activation function, the most commonly used one in the MLP is the sigmoid type, defined as:

$$f(x) = \frac{1}{1+e^{-x}} \qquad (3.2)$$

Where $y_k(n)$ and $y_{pk}(n)$ are the actual outputs and network predicted outputs, respectively.

$$E_{MSE} = \frac{1}{2M}\sum_{i=1}^{M}\left(y_i - y_{ip}(n)\right)^2 . \qquad (3.3)$$

-. Adaptation of weights (w_{ij}) and biases (b_i) in general:

$$w_{ij}(n+1) = w_{ij}(n) + \Delta w_{ij}(n). \quad (3.4)$$

$$b_j(n+1) = b_j(n) + \Delta b_j(n)\ . \quad (3.5)$$

where $\Delta w_{ij}(n) = \mu_1 x(n)\delta(n)\,, and\ \ \Delta b(n) = \mu_2\delta(n)$ (3.6)

and $\boldsymbol{\delta}$ is the derivative of error function with respect to the weight.

$$\delta = \left(\partial E/_{\partial W}\right) = \left(\frac{\partial E_{MSE}}{\partial W}\right). \quad (3.7)$$

The learning rate is represented by $\boldsymbol{\mu}$ **,** with $\mathbf{0} < \boldsymbol{\mu} < 1$,

II.2.2. Another performance used

Generally, we added to mean square error (MSE) performance analysis of the neural networks another performance which is accuracy. As mentioned in Eq. (3.8).To obtain the overall accuracy, it is calculated by taking the average classification for the three groups as follows: Standard statistical measures [33].

$$\text{Accuracy} = \left(\frac{\text{Number of correctly classified data}}{\text{Total number of data}}\right) * 100 \quad (3.8)$$

III. Results and Discussion

In this study, the performance for training data is included in order to select useful model such as architecture and different activation functions.

Table 1, describes the performance test for MLP with two hidden layers using learning algorithm as seen before.

Nodes number in hidden layers		Activation functions' used			
first hidden layer	Second hidden layer	tansig, logsig, purelin		tansig ,tansig, purelin	
		min error	max error	min error	max error
1 :9	1 to 40	0.0335	0.2538	0.0246	0.7408
10 :20	1 to 40	0 .0438	1.0423	0.0306	0.6130

Table. 1. Influence of number's node and Activation functions on MSE Error.

As shown in fig.1, and table .2 the performance achieved using the one hidden layer is considered to be better than those from two hidden layers. For this, we are varying the neuron's number from 1 to 100 in one hidden layer and we use different activation functions such as tansig , logsig and purelin .Then, we fixed iteration in number 20 and net.trainParam.lr=0.05 of the neural networks for the system (see fig.1).

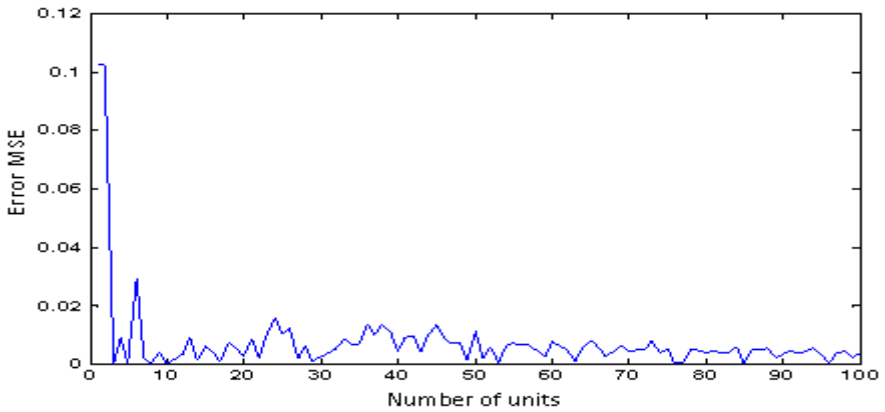

Figure1. Influence of the number of hidden units on error with one hidden layer

When we use one hidden layer in comparison to two hidden layers, we notice a better performance. According to rates achieved using the topology 3 and 5 units in only one hidden layer are 2**, 71E-09** and **1, 86E-09** see Fig .1[29]. But the two hidden layers performance did not achieve **0.0246** and **0.0306** as a maximum in this topology (5, 21)and (10, 14) respectively, we notice that the first and second numbers of this topology are number of neurons in first and second hidden layers respectively, see Table 1.

Unit number's	min Error	max Error	topology correspond of Error	respectively
1to 10	2,19E-12	**0 ,037265173**	3	1
11 to 20	6E-09	4,45E-09	17	14
21to 30	1,76E-24	7,67E-08	28	30
31 to 40	5,98E-20	5,49E-08	40	31
41 to 50	6,39E-21	1,08E-05	50	47
51 to 60	1,96E-21	5,67E-19	57	51
61 to 80	**3.47e-028**	2.61e-022	**75**	67

Table .2. Influence of number's node on error using one hidden layer.

Too name. Briefly the results approved the performance in only one hidden layer. For this, we focused on this topology. In addition, we will present the rest of results to augment number of iterations in order to obtain the maximum performance see table.2. After we tested this model to testing data empirical performance was discovered see fig.2.

Finally, our architecture selected is 75 nodes in hidden layer (18, 75, 1).Which gives MSE=**3.47e-028.** Figures 3, 4 show successfully the variation of the signal actual outputs and network predicted outputs in learning and testing base.

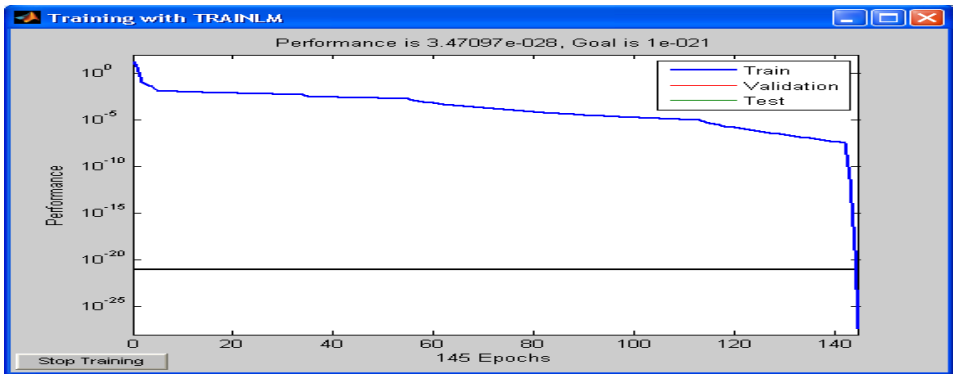

Figure.2.Evolution of the mean square error during the learning, validation and testing as a function number of iterations with a network configuration [12- 75- 1].

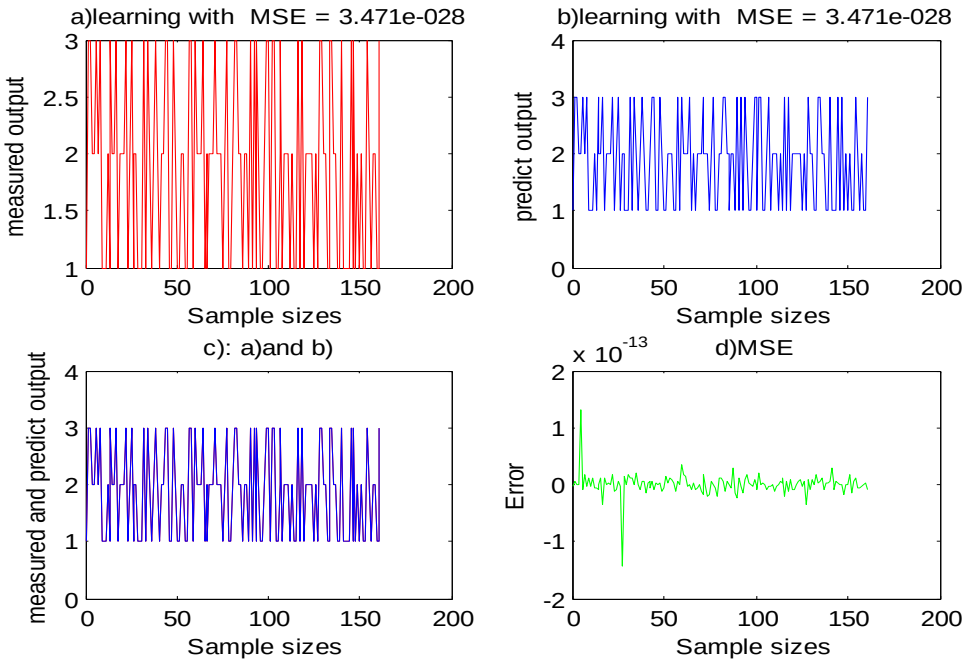

Figure 3. Variation of desired, calculated outputs of the three toxic gases and their error during learning.

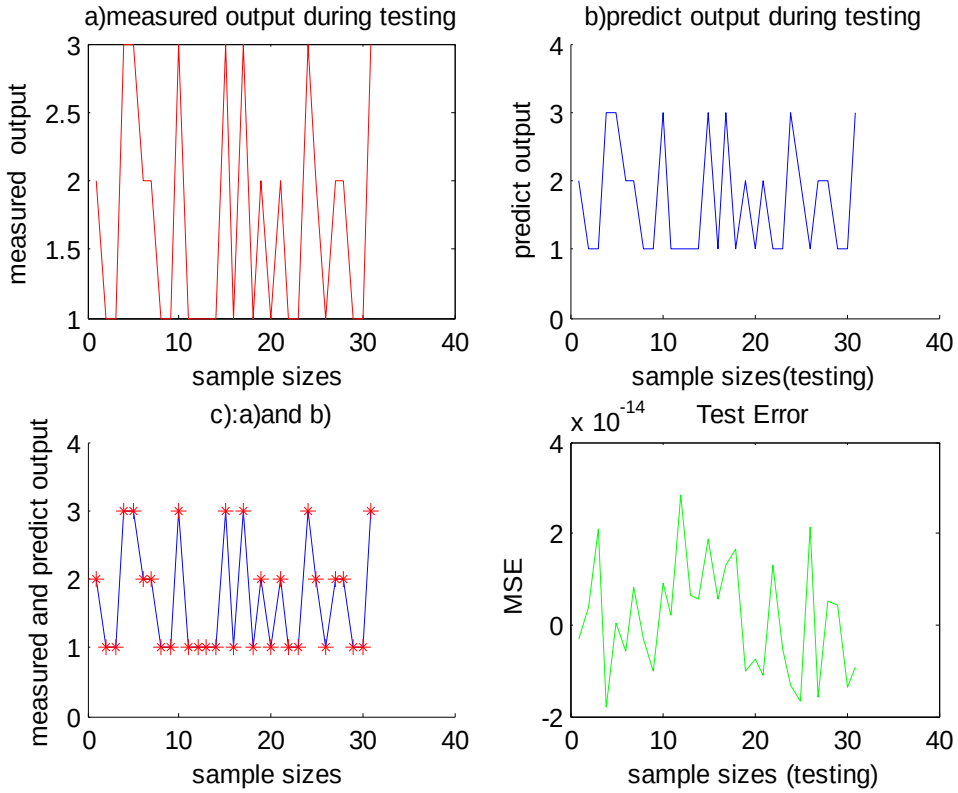

Figure.4. Variation of desired, calculated outputs of the three toxic gases and their error during testing.

This model is an additional to previous research [16-20] the use of MLP on-line type which verified the power of a part of our model concerning the selection of key parameters of MLPNN in one side, in other hand. The useful results are obtained in terms of prediction with perfect performance (see fig 4).this latter allows us to not mention the multiple linear regression method to not burden our paper [34-35].

IV. Conclusion

In this paper, the power of our MLPNN model using BP learning to predict the three toxic gases in complex conditions namely: two different gases and their mixture in low concentration, data base is reduced in160 samples size, and performance results must be hundred per cent.

The results of prediction are much more efficient in both of advantages; the first is optimizing the ANN architecture with one Hidden layer with three nodes in just 20 iterations which decrease the model size with the possibility to integrate the application field of an ordinary portable E-nose. Second, the model proved its stability when we augment the neuron and iteration number's ,which increase to be used in satisfied performance system for the security of indoor air quality.

References

[1] Akkoyunlu A, Ertürk F. Evaluation of air pollution trends in İstanbul. *Int J Environ Pollut*, 18, 2003,388–398.
[2] Karaca F, Ölmez I, Aras NK. A radiotracer method to study the transport of mercury (II) chloride from water to sediment and air. *J Radioanal Chem*, 259, 2004,223–226.
[3] Karaca F, Alagha O, Ertürk F. Application of inductive learning: air pollution forecast in Istanbul, Turkey. *Intell Autom Soft Co*, 11(4), 2005a ,207–216.
[4] MW Gardner, SR Dorling. Neural network modeling and prediction of hourly NOx and NO2 concentrations in urban air in London. *Atmospheric Environment*, vol 33, No 5. 1999, 709–719,.
[5] Berna, A. (2010). Metal oxide sensors for electronic noses and their application to food analysis. *Sensors*, 10, 3882–3910.
[6] E. Rumelhart, G.E. Hinton, All, Learning representations by back-propagating errors, *Nature* ,vol .322, 1986,533–536,.
[7] Y. Chauvin, D. E. Rumelhart (Eds.), Back propagation: Theory, Architectures, and Applications, Lawrence Erlbaum Associates, 1995.

[8] J. Ramesh , P.T. Vanathi, K. Gunavathi, Fault classification in phase-locked loops using back-propagation neural networks, *ETRI journal*,vol. 30, pp.546-553, 2008.
[9] P. Chandra and Y. Singh, "An activation function adapting training algorithm for sigmoidal feedforward networks". *Neurocomputing* 61, 2004,429–437..
[10] W. Duch and N. Jankowski, "Survey of neural transfer functions". *Neural Comput Appl 2*, 1999,163–212,.
[11] W. Duch and N. Jankowski, "Transfer functions": Hidden possibilities for better neural networks. *In 9th European symposium on artificial neural networks*, 2001, 81–94,.
[12] Y. Singh and P. Chandra, "A class +1 sigmoidal activation functions for FFANNs". *J Econ Dynamic Control* 28(1),2003,183–187.
[13] Negnevitsky, M.. Artificial Intelligence: a Guide to Intelligent System, 2nd Edition. *Addison-Wesley, England*,2005.
[1 4] Brezmes, J., Ferreras, B., Llobet , E., Vilanova, X., & Correig, X. Neural network based electronic nose for the classification of aromatic species. *Analytica Chimica Acta*, 348, 1997,503–509.
[15] M. Badura et al, Statistical assessment of quantification methods used in gas sensor system", *Sensors and Actuators B: Chemical* vol.188, November 2013, 815– 823.
[16] A .Lfakir ,Identification et Quantification d'une atmosphère gazeuse complexe à l'aide d'un système multi-capteurs intelligent .Application La détection de mélanges composés de H2S ,NO2,SO2 en atmosphère humide variable, thèse d'Université Metz, 2006.
[17] O.Helli .Multicapteurs de gaz pour la conception d'un nez électronique de surveillance de la pollution atmosphérique, thèse d'Université Metz (2003).
[18] K An ngo, Etude d'un système multiplicateur pour la détection sélective des gaz, thèse d'Université, université paul cesanne Aix Marseille III , 2006
[19] S.Ouhmad ,All, "Classification of toxic pollutant gases by the use of artificial neural networks type multilayer Perceptron", *XI the International Symposium on Environment, Catalysis and Process Engineering (ECGP'11) France, Villeneuve, d'Ascq*, , 26-28 June, 2013, p. 27.
[20] S.Ouhmad ,All "Real time identification of toxic gases based on artificial neural networks", *International Journal of Computational Engineering Research*, vol, 04 issue, 4,pp 67-72
[21] T.Seiyama,N.Yamazoe ,S.Yamauchi ,"Chemical Sensor Technology" *Elsevier Science Ltd*, Vol. 1, 2, 3 et 4. 1988.
[22] Bishop, C. M. (1995). Neural networks for pattern recognition. New York: Oxford University Press Inc...
[23] P. Arpaia, P. Daponte, D. Grimaldi, L. Michaeli, ANN-based error reduction for experimentally modeled sensors, IEEE Transactions on Instrumentation and Measurement 51 (February (1)) ,2002, 23–29.
[24] S. Haykin, Neural Network: A Comprehensive Foundation, McMillan, New York, 1994.
[25] N.K. Bose, P. Liang, Neural Network Fundamentals with Graphs, Algorithms and Applications, Tata *McGraw-Hill Publishing Company Ltd., New Delhi*, 2001.
[26] Principe, N.Euliano, C. Lefebvre," Neural and Adaptive Systems: Fundamentals Through Simulations", *John Wiley and Sons*, 1999.
[28] Duda, R. O, Hart, P. E., & Stock, D. G. Pattern classification. John Wiley & Sons. Exarchos, T. P., Tzallas, A. T., & Fotiadis, D.I.(2006). EEG transient event detection and classification using association rules. *IEEE Transactions on Information Technology in Biomedicine*, 10(3), 2001.
[29] Yu, C. C, & Liu, B. D. A backpropagation algorithm with adaptive learning rate and momentum coefficient. *In Proceedings of the 2002 international joint conference, neural networks, IJCNN '02* ,vol. 2, 2002,pp. 1218–1223).
[30] Yu, X., Efe, M. O., & Kaynak, O. A general backpropagation algorithm for feedforward Neural Networks learning. *IEEE Transactions on Neural Networks*, 13(1), 2002, 251–254.
[31] Bishop, C. M. Neural networks for pattern recognition. New York: Oxford University, 1995.
[32] D.E.Rumelhart, J.L.Mc Clelland, Parallel Distributed Processing. Foundations, Cambridge, MA, vol.1, 1986, MIT Press,
[33] T. Feyzullah, A comparative study on thyroid disease diagnosis using neural networks, *Expert Systems with Applications* ,36 (1) , 2009, 944–949.
[34] D. Gacquer a,b,c, V.Delcroix a,b,c, F.Delmotte a,d,e, S.Piechowiak a,b,c, Comparative study of supervised classification algorithms for the detection of atmospheric pollution, *Engineering Applications of Artificial Intelligence* 24 ,2011,1070–1083.
M. Baduraa, A. Szczureka, P.M. Szecówkab, Statistical assessment of quantification methods used in gas sensor system, *Sensors and Actuators B* ,188 ,2013 , 815– 82
[35] Duch, W., Jankowski, N, Transfer functions: Hidden Possibilities for Better Neural Networks. *In: 9th European Symposium on Artificial Neural Network*. Bruges 2001, 81-94.